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Methodologic Issues in Using Land Cover Data to Characterize Living Environments of Geocoded Addresses

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Estes et al. (2009) presented an interesting analysis of the relationship between blood pressure levels of individuals in four metropolitan regions and their living environments. Remotely sensed data was used to determine urban, suburban, and rural living environments as well as day/night land surface temperatures (LST). These remotely sensed data sets are readily available nationally, increasing the replicability and consistency of the methods.

Estes et al. (2009) characterized living environments using the 2001 National Land Cover Dataset (NLCD; Homer et al. 2004). Detailed land cover classes were reclassified into broad categories of urban, suburban, and rural, and the original 30-m resolution raster data was resampled to a 1-km grid using a majority filter to match the resolution of the LST data. Residential addresses were geocoded and their location compared to the 1-km grid cell values to establish the living environment variables. There are several problems that result from this particular methodology, which I address below.

First, Estes et al. (2009) geocoded the residential addresses using SAS/GIS geocoding software which employs TIGER data (SAS 2010) from the U.S. Census Bureau for street geocoding. The positional accuracy of TIGER data is not very good (e.g., Zandbergen 2008), and street geocoding in general is not very accurate (Cayo and Talbot 2003; Zandbergen 2009). The street geocoded location of the residence of a particular individual is therefore not very likely to fall inside the same 30-m grid cell as the true location of the residence. For example, the median error of typical street geocoding is in the order of 30–60 m for urban areas, about double that for suburban areas and much larger in rural areas (Cayo and Talbot 2003; Zandbergen 2009). This is likely to introduce a substantial number of misclassifications. Any point-in-raster overlay where the positional error of the points is of the same order of magnitude as the raster resolution is not very reliable, and the degree of misclassification will vary with the spatial heterogeneity of the land cover data.

Second, the positional errors in street geocoding are not random in nature. Typical street geocoding employs a standard offset from the roads in the placement of the geocoded locations. In many areas, however, the actual residence is located at much greater distances, especially in rural areas. In the 2001 NLCD land cover data, many rural and suburban roads are classified as developed open space. This means that geocoded rural addresses will typically fall on this land cover type, while the actual residence is located on an agricultural or vegetated category. This adds to the occurrences of misclassifications, especially between suburban and rural.

Third, the resampling of the original land cover data from 30 m to 1 km using a majority filter has the undesirable effect that small clusters of one land cover type that are surrounded by larger areas of other types will simply disappear. Estes et al. (2009) clearly acknowledged this and compared the classifications resulting from different resolutions; when resampling from 30 m to 1 km, only 63% of all locations were classified the same. This effect of resampling will vary between study areas. For example, urban development in Atlanta, Georgia, is relatively fragmented and the resampling results in a substantial reduction of the total area (from 2.0% of the study area in the original 30-m grid to 0.94% in the 1-km grid). A more compact urban development pattern such as Chicago, Illinois, is more robust to the effect of resampling.

The resampling does overcome some of the misclassifications introduced by the errors in street geocoding. In effect, the land cover type at the exact location of the geocoded address is no longer of greatest interest, and instead the “majority” land cover of the surrounding area is used. However, the effects of street geocoding errors and resampling will vary greatly between study areas, reducing the robustness of the final classifications of study subjects and introducing potential bias.

One approach to overcome some of these problems is to use the 2001 impervious cover data, which is provided as a complement to the 2001 NLCD land cover data. Imperviousness is classified between 0 and 100% and corresponds closely to the different land cover types, albeit providing more detail. The benefit of using impervious cover is that during resampling a simple averaging filter can be used instead of a majority filter. This type of filter produces unbiased results that are not dependent on the spatial heterogeneity of the landscape or the scale of resampling. Similar urban, suburban, and rural categories can be identified and will remain more robust under various resampling scenarios.

The availability of moderate to high resolution remotely sensed data at national and global scales is providing unprecedented opportunities to compare health observations to environmental variables, including land cover and climatic factors. When combining data from different sources, great care should be taken to ensure the accuracy of the input is sufficient to produce reliable results given the specific analysis methods employed. Street geocding in particular has been underestimated as a source of positional error. In addition, when resampling methods are employed to produce data sets of matching resolution, robust methods are needed to avoid the unnecessary introduction of noise and bias.

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Paul A. Zandbergen
Department of Geography
University of New Mexico
Albuquerque, New Mexico
E-mail: zandberg@unm.edu

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Using Land Cover Data to Characterize Living Environments of Geocoded Addresses: Estes et al. Respond

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We appreciate the insightful and informative letter about the methodology used in our article (Estes et al. 2009). We agree with Zandbergen about the methodology employed by the SAS/GIS software used for geocoding the REGARDS (REasons for Geographic and Racial Differences in Stroke) participants. As one of the REGARDS study goals, we plan to re-geocode the participants using a more accurate method. However, because our article focused on classifying the “living environment” (defined as urban, suburban, and rural) and because most people do not spend the majority of their time at their house or within the raw resolution area (30 m × 30 m), the geocoding errors that are in the levels of tens of meters become less relevant. This is true especially when we resample to a coarser resolution (1 km vs. 30 m), as we did in our methodology to characterize the participants' living environment.

With respect to the misclassification that may be introduced due to the resolution used to classify participants, Zandbergen is correct that resampling to different resolutions did change the classification of the participants. However, the results of the analyses were consistent regardless of the resolution of the classification, indicating that while this may influence the exposure itself, it does not influence the relationship between the exposure and the outcome.

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Maurice G. Estes Jr.
Mohammad Z. Al-Hamdan
William Crosson
Sue M. Estes
Universities Space Research Association
NASA–Marshall Space Flight Center
National Space Science and Technology Center
Huntsville, Alabama
E-mail: maury.g.estes@nasa.gov

Dale Quattrochi
Earth Science Office
NASA–Marshall Space Flight Center
National Space Science and Technology Center
Huntsville, Alabama

Shia Kent
Leslie Ain McClure
Department of Biostatistics
University of Alabama–Birmingham
Birmingham, Alabama

Reference

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What Can Affect AOD–$PM_{2.5}$ Association?

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Although satellite remote sensing has advanced significantly in recent years, there are inherent weaknesses in the use of this technology. The association between satellite-based aerosol optical depth (AOD_S) and air pollution monitored on the ground can be influenced by a number of factors. In their article, Paciorek and Liu (2009) highlighted the weaknesses of AOD_S to predict the spatial distribution of fine particulate matter ≤ 2.5 μm in aerodynamic diameter ($PM_{2.5}$). It is a timely article given the increasing importance of indirect methods, including satellite data, to estimate air quality because of scarce and ad hoc spatial–temporal coverage of air pollution monitored by federal regulatory methods. It is important that the robustness of these methods is evaluated, and Paciorek and Liu's article is such an attempt. However, they failed to address the role of five major factors that can influence the AOD_S–$PM_{2.5}$ association. These factors include decomposition of AOD_S by aerosol types, mismatch in spatial–temporal resolution, collocation and integration of AOD_S and $PM_{2.5}$ data, and control for spatial–temporal structure in the statistical model. Consequently, the weaknesses in Paciorek and Liu's study lead me to question their findings.

The columnar measurement of AOD_S consists of aerosols generated by anthropogenic (human) sources (AOD_{Sh}), such as emissions from industries and vehicles, and natural sources (AOD_{Sn}), such as water vapor or dust in the air. AOD_{Sn} that constitutes a large fraction of AOD_S is influenced by moving large air masses and observes a strong spatial and temporal structure. The concentration of $PM_{2.5}$, however, can vary significantly within short distances. Therefore, there is a significant mismatch in the magnitude and extent of spatial and temporal variability of AOD_{Sn} and AOD_{Sh}; without an adequate control for AOD_{Sn}, it is difficult to develop a reliable $PM_{2.5}$ predictive model using AOD_S (Kumar et al. 2008).

Paciorek and Liu (2009) recognized that the spatial–temporal resolutions of AOD_S and $PM_{2.5}$ they used were different, but they did not address how the mismatch in the spatial–temporal resolutions of these data can influence their association. The spatial resolutions of MISR (multiangle imaging spectroradiometer), MODIS (moderate resolution imaging spectroradiometer), and GEOS (geostationary operational environmental satellite) AOD were 17.6 km, 10 km, and 4 km, respectively, and $PM_{2.5}$ data were point measurements aggregated across 24 hr. A recent study suggests the strength of the AOD_S–$PM_{2.5}$ association diminishes with the increase in time interval used for their aggregation (Kumar et al. 2007). It would have been useful for Paciorek and Liu (2009) to document the implications of the spatial–temporal resolutions and aggregation of AOD and $PM_{2.5}$ (data they used) on their findings.

AOD_S retrieval and $PM_{2.5}$ are not available on the same days: AOD_S retrieval is not possible on cloudy days, and $PM_{2.5}$ data are recorded every third or sixth day. It seems that Paciorek and Liu (2009) averaged all AOD_S at 4-km pixel (i.e., 16 km^2 area; monthly and yearly) and all $PM_{2.5}$ (in the pixels where a monitoring station was situated). This could have resulted in a weak association between AOD_S and $PM_{2.5}$, because there were systematic temporal gaps in both AOD_S and $PM_{2.5}$ data sets. A reasonable approach to address this problem is to aggregate AOD_S-$PM_{2.5}$ data for those days only when both AOD_S and $PM_{2.5}$ are available.

Paciorek and Liu's method for aggregating 17.6-km and 10-km AOD_S to a 4-km pixel seems problematic. First, a radiative transfer model is used to retrieve AOD_S (Remer et al. 2006) which removes pixels with the upper 50% and lower 20% of the reflectance values. This removal can be systematic. For example, pixels with high reflectivity (such as buildings and roads) are more likely to be removed than the vegetated pixels (i.e., pixels under vegetation canopy). Thus, the centroid of a 10-km AOD_S pixel may not represent the AOD_S value for the entire 10-km area. Second, AOD_S registers a strong spatial–temporal autocorrelation. Thus, time–space kriging that utilizes large number of data points is appropriate for AOD_S aggregation rather than a single AOD_S value to avoid an area specific bias.

The robustness of AOD_S retrieval is evaluated by its comparison with the AOD recorded by sunphotometers at AERONET sites (AOD_A) (NASA 2007). The spatial resolution at which AOD_S is retrieved and the spatial–temporal intervals within which these data are aggregated may directly influence its comparison with the AOD_A . This, in turn, can influence the association between AOD_S and $PM_{2.5}$. Recent literature suggests that 1-km and 5-km AOD_S observe a significantly better association with $PM_{2.5}$ monitored on the ground than the 10-km AOD_S (Kumar et al. 2007; Li et al. 2005). Therefore, the optimal spatial resolution of AOD_S retrieval and the optimal spatial and temporal intervals for aggregating these data are critically important for developing time–space resolved estimates of air quality with the aid of AOD_S.

Because meteorologic conditions are largely influenced by the prevailing air masses and do not vary significantly within thousands of miles for a short period of time, the AOD_{Sn} component of AOD_S is likely to have a strong spatial–temporal structure. $PM_{2.5}$ that constitutes particulate mass associated with anthropogenic factors, however, varies significantly within short distances from emission sources. Therefore, to develop a $PM_{2.5}$ predictive model it is important that only AOD_{Sh} is used instead of AOD_{Sn}. If such data are not available, an alternative is to indirectly control for AOD_{Sn} and its associated spatial–temporal structure. Otherwise the predicted $PM_{2.5}$ surface is likely to have an unrealistic spatial trend, as reported by Paciorek and Liu (2009), as well as unrealistic temporal trends.

The author declares he has no competing financial interests.

Naresh Kumar
University of Iowa-Geography
Iowa City, Iowa
E-mail: naresh-kumar@uiowa.edu